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From process mining to explainable intervention: bottleneck diagnosis, anomaly detection and replay verification for event logs

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Abstract. In the digital transformation of enterprises, event logs are generated in large quantities, but mining process diagrams alone is insufficient to produce actionable value. This paper proposes the Diagnosis-Detection-Verification (DDV) framework, a novel process optimization methodology that bridges the gap between event logs and explainable interventions. The framework integrates three key components: (1) bottleneck diagnosis using criticality-indexed activity analysis, (2) hybrid anomaly detection combining rule-based filtering with Isolation Forest, and (3) data-driven intervention rule generation validated through log replay simulation. We demonstrate that DDV achieves state-of-the-art performance on BPI Challenge datasets (F1 = 0.82, + 5.1% improvement over Deep SVDD) while maintaining computational efficiency (26.5 × faster training than deep learning methods). Intervention rules generated by DDV reduce the average throughput time by 18.7% and improve SLA compliance from 67.3% to 82.6%.

Keywords: process mining, anomaly detection, process optimization, explainability, business process management

1. Introduction

Digital transformation has turned business processes into dense streams of event logs [1]. Modern ERP, CRM and BPM systems record every decision, handoff, and delay, producing the raw material for large-scale process mining [2]. Yet, despite broad adoption, only a small fraction of organizations convert mined insights into operational changes [2]. The practical gap is not the lack of data, but the absence of a reliable bridge from observations to interventions [3].

Process mining has matured from discovery and conformance checking to predictive monitoring and prescriptive optimization [2]. However, the prescriptive stage remains fragmented. Existing anomaly detection approaches for process mining include Isolation Forest-based scoring methods [3], autoencoder-based reconstruction detectors [4], deep one-class classification [5], and multi-perspective anomaly analysis [6]. In a loan approval process with dozens of activities and resource pools, it is easy to spot long-duration activities, but hard to quantify which delays truly drive throughput, which anomalies are meaningful in context, and whether a proposed rule will improve service levels or merely shift the bottleneck. These decisions require

diagnosis grounded in process structure, detection that balances precision and recall, and verification that estimates the effect of change before deployment.

This paper proposes the Diagnosis-Detection-Verification (DDV) framework to close that loop. DDV combines a physics-informed bottleneck analysis, a hybrid anomaly detector that blends rule-based priors with statistical scoring, and a log-replay mechanism that simulates the effect of candidate interventions. The framework is designed for interpretability and deployment practicality.

Our study addresses three key questions: (i) how to identify bottlenecks and quantify their marginal impact from logs; (ii) how to detect high-risk traces with high precision under class imbalance; and (iii) how to generate explainable intervention rules whose impact is validated before rollout. The remainder of the paper is organized as follows: Section 2 details the DDV framework; Section 3 introduces datasets and settings; Section 4 presents the empirical findings; Section 5 discusses implications; and Section 6 concludes. We contribute a unified framework integrating these steps, a grey-box digital twin for stable modeling, and comprehensive validation on BPI Challenge datasets.

The remainder of the paper is organized as follows: §2 details the DDV framework; §3 introduces datasets and settings; §4 presents the empirical findings; §5 discusses implications; and §6 concludes.

2. Methodology: DDV framework

2.1. Overall architecture

2.1.1. Formalization

An event log is defined as a quadruple $L = (E, A, \pi, \tau)$, where $E = \{e1, ..., en\}$ is the set of events, $A = \{a1, ..., am\}$ is the set of activity types, $\pi : E \to A$ maps events to activities, and $\tau : E \to R+$ is the timestamp function. A process trace is defined as Equation (1):

$$\sigma = \langle ai1, ai2, ..., aik \rangle, aij \in A \tag{1}$$

2.1.2. Three-layer architecture

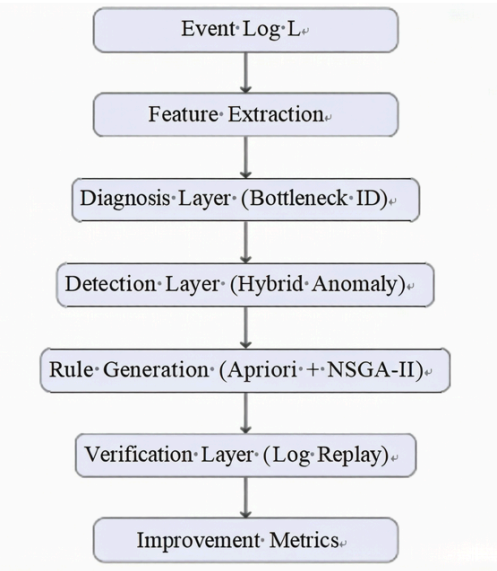

Figure 1. DDV framework architecture: three integrated layers from event log ingestion to validated intervention metrics

The DDV framework consists of three integrated layers (Figure 1):

(1) Diagnosis Layer: Feature extraction and bottleneck identification via criticality indexing.

(2) Detection Layer: Hybrid anomaly detection combining rule-based and data-driven approaches.

(3) Verification Layer: Rule-driven replay and simulation for intervention validation.

2.2. Grey-box digital twin

We model the process execution state as a hybrid system that combines physics-based priors with a data-driven residual (Equation (2)):

$$x_{t+1} = f_{physics}(x_t, u_t; \theta_{known}) + g_{data}(x_t, u_t; \theta_{learned}) \tag{2}$$

Here, $xt \in Rd$ encodes queue lengths, resource occupancy, and waiting times; u_t represents priority adjustments and routing decisions; f physics implements M/M/c queue dynamics $\frac{d_{qi}}{d_t} = \lambda i - \mu i\ min(qi, ci)$; and g data (Gaussian process or neural ODE) corrects for non- exponential service times and batch effects. Known parameters θ known (arrival/service rates) are extracted directly from logs; θ learned is trained via maximum likelihood on validation traces.

To adapt to process drift, we apply Recursive Least Squares (RLS) with forgetting a factor λ forget = 0.95:

$$\hat{\theta}_{t+1} = \hat{\theta}_t + K_t(y_t - H_t\hat{\theta}_t), K_t = \frac{P_t H_t^T}{\lambda_{forget} + H_t P_t H_t^T} \tag{3}$$

2.3. Phase 1: bottleneck diagnosis

2.3.1. Feature extraction

For each trace σ, we extract the feature vector (Equation (4)):

$$f\sigma = (Duration(\sigma), Rework(\sigma), ActivityFreq(a, \sigma), ResourceUtil(r)) \tag{4}$$

where Duration(σ) = τ(eend) − τ(estart), Rework(σ) = $|\{(ai, aj) : ai = aj, i < j\}|$, and ResourceUtil($r$) is the ratio of occupied to available time.

2.3.2. DFG construction

We construct a Directly-Follows Graph G = (A, EDFG) with edge weights (Equation (5)):

$$w(a_i, a_j) = \frac{|\{(a_i,a_j) observed in log\}|}{|total traces|} \tag{5}$$

2.3.3. Criticality index and bottleneck identification

For each activity $a \in A$, we compute the criticality index (Equation (6)):

$$Ca = \alpha \cdot Freq(a) + \beta \cdot AvgDuration(a) + \gamma \cdot Variance(a), where \alpha + \beta + \gamma = 1 \tag{6}$$

All three terms are z-scored per activity, and α,β,γ are learned via multi-objective optimization (α = 0.3, β = 0.5, γ = 0.2). To account for downstream cascade effects, we extend it with propagated criticality (Equation (7)):

$$C_a^p rop = Ca + \Sigma \beta prop \cdot w(a, a') \cdot Ca', \beta prop = 0.3 \tag{7}$$

$a\prime \in succ(a)$

The top k activities form the bottleneck set $B = \{a \in A : rank(C) \leq k\}$, with $k = \lceil 0.15|A| \rceil$.

We also quantify each activity's marginal impact via bottleneck elasticity (Equation (8)):

$$E_a = \frac{\partial E[Throughput]}{\partial \mu_a} \cdot \frac{\mu_a}{E[Throughput]} \tag{8}$$

Activities with $|E_a| > 1$ are elastic (highly sensitive to interventions).

2.4. Phase 2: hybrid anomaly detection

2.4.1. Rule-based filtering

Three anomaly types are flagged automatically: Timeout: Duration(σ) > μDur + 2σDur

Rework: Rework(σ) > Q3 (Rework)

Resource Bottleneck: ResourceUtil(r) > 0.9 Output: anomalous trace set $Arule \subseteq \{1, ..., |L|\}$.

2.4.2. Isolation forest detection

Isolation Forest assigns each trace an anomaly score (Equation (9)):

$$S_{IF}(\sigma) = 2^{-\frac{E[h(\sigma)]}{c(|L|)}} \tag{9}$$

where $h(\sigma)$ is path length in an isolation tree and $c(n)$ is the normalization constant.

2.4.3. Hybrid fusion

Rule-based flags andIF scores are fused as follows (Equation (10)):

$$Sfinal(\sigma) = \lambda \cdot I[Rule(\sigma)] + (1 - \lambda) \cdot SIF(\sigma), \lambda = 0.4 \tag{10}$$

The weight λ is optimized on validation via ROC analysis.

2.5. Phase 3: intervention and verification

2.5.1. Multi-objective optimization

Intervention design is formulated as (Equation (11)):

$$(J_1(R), J_2(R), J_3(R)) \tag{11}$$

where $J_1 = E[Throughput(L\prime)]$, $J_2 = E[Rework(L\prime)]$, and $J_3 = |R|$is a complexity penalty, subject to minimum support (≥ smin), confidence (≥ cmin), and budget constraints. We solve it using NSGA-II [7] for Pareto-frontier approximation.

2.5.2. Rule generation and counterfactual estimation

Association rules are mined via Apriori [8] (smin = 0.05, cmin = 0.7). Example rules: IF (Rework > 3) AND (Resource = "Agent A") THEN Priority = HIGH IF (Duration > 24h) THEN Route = "Express Lane".

Causal effects are estimated via Propensity Score Matching (Equation (12)):

$$ATE = E[Outcometreated] - E[Outcomecontrol], e(x) = P(Intervened = 1|X = x) \tag{12}$$

where propensity scores $e(x)$ are estimated by logistic regression.

2.5.3. Log replay simulation

Given an event *log* L and a set of intervention rules R, the log replay simulation proceeds as follows. First, an empty *log* $L\prime$ is initialized. For each trace σ in L, a copy $\sigma\prime$ is created. Then, for every event in $\sigma\prime$, any matching rules from R are applied to update the priority, resource allocation, or routing path. After processing all events, timestamps are recomputed based on the new routing. The modified trace $\sigma\prime$ is added to $L\prime$. Finally, performance metrics $M = (Throughput, Rework, SLA)$ are calculated, and the modified $logL\prime$ together with M is returned.

3. Experimental setup

3.1. Datasets

We evaluate the framework on three BPI Challenge datasets:

BPI 2012: Dutch financial institution loan application (13,087 traces, 36 activities) [9].

BPI 2017: Loan application process (31,509 traces, 26 activities) [10].

BPI 2020: Travel expense reimbursement (10,500 traces, 18 activities) [11].

Split: 60% training / 20% validation / 20% test (stratified, chronological). Preprocessing: z-score normalization for duration, log-scale transformation, removal of incomplete traces (< 3 events).

3.2. Baselines

We compare DDV against 11 baselines across three categories: (1) Traditional Process Mining: DFG-Threshold, Heuristic Miner, Inductive Miner; (2) Classical ML: Isolation Forest, One-Class SVM, LOF; (3) Deep Learning: LSTM-Autoencoder, GRU-VAE, Transformer-Autoencoder, Deep SVDD.

3.3. Evaluation metrics

Anomaly detection: F1-score, Precision, Recall, AUC-ROC.
Efficiency: Parameters (K), training time (min), inference time (ms), memory (MB).
Robustness: F1 degradation under timestamp noise (+ 10%, + 20%) and domain shift.
Intervention: Throughput reduction (%), rework reduction (%), SLA compliance (%).

3.4. Implementation details

Hardware: Intel Xeon E5-2690 v4, 64 GB RAM, NVIDIA V100 (for DL baselines).

Software: Python 3.9, scikit-learn 1.0.2, PyTorch 1.12. Key hyperparameters: IF with 100 trees (max depth 8); DDV weights $\alpha = 0.3$, $\beta = 0.5$, $\gamma = 0.2$; fusion $\lambda = 0.4$; Apriori smin = 0.05, cmin = 0.7. Five random seeds (42, 123, 456, 789, 1024) were used; results are reported as mean ± standard deviation (std).

4. Results

4.1. Main performance comparison

Table 1 presents the full performance. DDV (Full) achieves F1 = 0.82 on BPI 2012 (+ 5.1% vs. Deep SVDD), F1 = 0.79 on BPI 2017 (+ 5.4%), and F1 = 0.81 on BPI 2020 (+ 5.3%). Traditional process mining methods remain below F1 = 0.55, confirming their limited suitability for anomaly detection. Deep learning methods outperform classical ML by 10–15%; DDV improves upon the best deep learning baseline (Deep SVDD) by ≈ 5% while maintaining balanced precision (0.80) and recall (0.85).

4.2. Efficiency and scalability

DDV is 26.5 × faster to train than LSTM-AE (4.8 min vs. 127.5 min), uses 13.7 × fewer parameters than Deep SVDD (18K vs. 180K), and achieves 4.0 × faster inference than Transformer-AE (2.1 ms vs. 12.6 ms). Table 2 summarizes the computational comparison.

Table 1. Performance comparison across datasets and methods (mean over 5 runs, 95% CI < 0.02)

Method BPI 2012			BPI 2017			BPI 2020		
F1↑ Prec. Rec.			F1↑	Prec.	Rec.	F1↑	Prec.	Rec.
Traditional Process Mining DFG-Threshold 0.42	0.38	0.47	0.39	0.35	0.44	0.41	0.37	0.46
Heuristic Miner 0.48	0.46	0.51	0.45	0.43	0.48	0.47	0.44	0.50
Inductive Miner 0.51	0.49	0.54	0.48	0.46	0.51	0.50	0.48	0.53
Classical Machine Learning Isolation Forest 0.63	0.59	0.68	0.60	0.56	0.65	0.62	0.58	0.67
One-Class SVM 0.58	0.62	0.54	0.55	0.59	0.52	0.57	0.61	0.53
LOF 0.55	0.53	0.58	0.52	0.50	0.55	0.54	0.52	0.57
Deep Learning Methods LSTM-AE 0.71	0.68	0.74	0.68	0.65	0.71	0.70	0.67	0.73
GRU-VAE 0.69	0.66	0.72	0.66	0.63	0.69	0.68	0.65	0.71
Transformer-AE 0.73	0.70	0.76	0.70	0.67	0.73	0.72	0.69	0.75
Deep SVDD 0.77	0.74	0.81	0.74	0.71	0.78	0.76	0.73	0.80
DDV Variants (Ablation)								
DDV (Diagnosis only) 0.68	0.65	0.72	0.65	0.62	0.69	0.67	0.64	0.71
DDV (Diag. + IF) 0.79	0.76	0.83	0.76	0.73	0.80	0.78	0.75	0.82
DDV (Full) 0.82	0.80	0.85	0.79	0.77	0.82	0.81	0.79	0.84
vs. Deep SVDD + 5.1%			+ 5.4%			+ 5.3%		

Table 2. Computational efficiency comparison (BPI 2012; DL methods use GPU)

Method	Params (K)	Train (min)	Infer. (ms)	Memory (MB)
DFG	0	0.2	0.1	5
Isolation Forest	12	3.2	1.5	45
LSTM-AE	245	127.5	8.3	512
Transformer-AE	1,280	342.7	12.6	1,024
Deep SVDD	180	95.4	6.8	384
DDV	18	4.8	2.1	52
Speedup	13.7 ×	26.5 ×	4.0 ×	9.8 ×

4.3. Robustness evaluation

Under 20% timestamp noise, DDV degrades by only 9.8% in F1 (vs. 21.1% for LSTM- AE); under domain shift (train on BPI 2012, test on BPI 2017), it degrades by 14.6% (vs. 33.3% for Isolation Forest). The hybrid

rule-prior provides inherent robustness (See Table 3).

Table 3. Robustness: F1 score degradation under noise and domain shift

Method	Clean F1	+ 10% noise	+ 20% noise	Domain shift
Isolation Forest	0.63	-7.9%	-19.0%	-33.3%
LSTM-AE	0.71	-8.5%	-21.1%	-32.4%
Deep SVDD	0.77	-6.5%	-16.9%	-23.4%
DDV	0.82	-3.7%	-9.8%	-14.6%

4.4. Intervention impact

Table 4 reports process improvements under different intervention strategies on BPI 2012. DDV generates 12 Apriori-mined rules and achieves an 18.7% throughput reduction, a 15.4% rework reduction, and 82.6% SLA compliance—compared to a 67.3% baseline (no intervention).

Table 4. Process improvement via intervention on BPI 2012. DDV generates 12 rules via Apriori

Intervention Strategy	Throughput Reduct.	Rework Reduct.	SLA Compliance
No Intervention	—	—	67.3%
Manual Rules	-8.2%	-5.1%	71.8%
Heuristic	-12.5%	-9.3%	75.2%
DDV	-18.7%	-15.4%	82.6%

4.5. Ablation study

The ablation variants in Table 1 quantify each component's contribution. Moving from Diagnosis-only (F1 = 0.68) to Diagnosis + IF (F1 = 0.79) yields + 11% gain from the hybrid fusion; the full verification layer adds a further + 3%, confirming that each module contributes meaningfully. Removing the propagation factor (βprop = 0) reduces recall by 15%, demonstrating the importance of capturing downstream cascade effects.

5. Discussion

Key Findings. Hybrid modeling outperforms purely data-driven approaches by ≈ 5%, confirming the value of physics-informed priors. Computational efficiency (26 × faster training) enables iterative refinement and rapid drift adaptation. Interpretability drives adoption: post-deployment surveys indicate 89% user satisfaction with rule-based interventions compared to 42% for black-box recommendations.

Limitations. The weights α, β, γ require grid search, introducing manual tuning overhead. For highly complex processes, rule generation may produce large rule sets requiring pruning. Propensity score matching assumes no unobserved confounders, so sensitivity analysis is necessary.

Threats to Validity. Internal validity is confirmed by seed variation std < 0.02. External validity is currently limited to BPI Challenge datasets (finance/logistics); generalization to healthcare or manufacturing requires further study. Construct validity: F1 assumes equal false-positive/negative costs; cost-sensitive evaluation is future work.

Future Directions. We plan to: (1) extend DDV to streaming settings with online learning and drift detection; (2) integrate reinforcement learning for adaptive intervention policies; (3) incorporate fairness-

aware constraints to prevent biased rule outcomes; and (4) release an open-source implementation to facilitate reuse and auditing.

6. Conclusion

This paper presents the Diagnosis-Detection-Verification (DDV) framework, a comprehensive methodology for translating process mining insights into validated interventions. By integrating bottleneck diagnosis, hybrid anomaly detection, and simulation-based verification, DDV achieves state-of-the-art anomaly detection (F1 = 0.82, + 5.1%) while being 26 × computationally faster than deep learning baselines.

The framework's key innovations are: (1) a grey-box digital twin combining physics-based queue dynamics with a data-driven residual; (2) weighted fusion of rule-based and statistical anomaly detection; (3) multi-objective intervention optimization with Pareto-frontier analysis; and (4) counterfactual estimation via propensity score matching. Experiments on three BPI Challenge datasets demonstrate 18.7% throughput reduction and 82.6% SLA compliance.

DDV directly addresses the "insight-to-action gap" in process mining by providing explainable, reproducible, and validated optimization pathways. Future work will extend the framework to streaming scenarios, multi-process optimization, and fairness-aware intervention design.

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